# Online sentiment towards iconic species

Fink, Christoph

2020-01

Fink , C , Hausmann , A & Di Minin , E 2020 , ' Online sentiment towards iconic species ' , Biological Conservation , vol. 241 , 108289 . https://doi.org/10.1016/j.biocon.2019.108289

http://hdl.handle.net/10138/312301
https://doi.org/10.1016/j.biocon.2019.108289

ARTICLE IN PRESS

Biological Conservation xxx (xxxx) xxxx

Contents lists available at ScienceDirect

Biological Conservation

journal homepage: www.elsevier.com/locate/biocon

# Online sentiment towards iconic species

Christoph Fink[a,b,*], Anna Hausmann[a,b], Enrico Di Minin[a,b,c]

[a] Helsinki Lab of Interdisciplinary Conservation Science, Department of Geosciences and Geography, University of Helsinki, Finland
[b] Helsinki Institute of Sustainability Science (HELSUS), University of Helsinki, Finland
[c] School of Life Sciences, University of KwaZulu-Natal, Durban, South Africa

ARTICLE INFO

*Keywords:*
Digital conservation
Culturomics
Illegal wildlife trade
Natural language processing
Social media
Sentiment analysis

ABSTRACT

Studies assessing online public sentiment towards biodiversity conservation are almost non-existent. The use of social media data and other online data sources is increasing in conservation science. We collected social media and online news data pertaining to rhinoceros, which are iconic species especially threatened by illegal wildlife trade, and assessed online sentiment towards these species using natural language processing methods. We also used an outlier detection technique to identify the most prominent conservation-related events imprinted into this data. We found that tragic events, such as the death of the last male northern white rhinoceros, Sudan, in March 2018, triggered the strongest reactions, which appeared to be concentrated in western countries, outside rhinoceros range states. We also found a strong temporal cross-correlation between social media data volume and online news volume in relation to tragic events, while other events only appeared in either social media or online news. Our results highlight that the public is concerned about biodiversity loss and this, in turn, can be used to increase pressure on decision makers to develop adequate conservation actions that can help reverse the biodiversity crisis. The proposed methods and analyses can be used to infer sentiment towards any biodiversity topic from digital media data, and to detect which events are perceived most important to the public.

## 1. Introduction

Large amounts of information, including nature-related content, are created and shared daily on social media and other digital platforms. Digital conservation is the field of conservation science that uses text, visual and audio-visual content mined from digital sources to investigate human-nature interactions (Arts et al., 2015; Di Minin et al., 2015a, 2015b; Ladle et al., 2016). Conservation culturomics, for instance, uses quantitative analyses of word frequencies in large corpora of digital texts to study people's engagement with nature (Ladle et al., 2016). Analyzing human-nature interactions from digital data can help identify opportunities to support biodiversity conservation and mitigate threats (Di Minin et al., 2015a, 2015b)

Digital media data is, however, typically extensive in volume and its texts contain mostly unstructured information. The texts are composed in natural language, and often use colloquial language, dialect terms or abbreviations. This makes it difficult to effectively identify and extract relevant information (Li, 2018). In recent years, increased computational resources and a cultural change towards more open web services has made it comparably straight-forward to collect data and compile general metrics (e.g. information on volume and use) for assessing public interest for biodiversity (see e.g. Mittermeier et al., 2019). These metrics, however, are limited in providing insights on the actual content and meaning of the collected information. Increasingly, machine learning methods are being used to automatically detect and identify user-generated text and visual content pertaining to human-nature interactions (Di Minin et al., 2015b, 2018, 2019).

Natural language processing (NLP) is a sub-field of computer science in which methods are being developed to understand and synthesize language, for instance digital texts (Chowdhury, 2005). Sentiment analysis and opinion mining are natural language processing methods used to assess the attitude expressed in a text (Liu, 2012; Pang and Lee, 2008). Popular applications include the assessment of the public's attitudes and appreciation (e.g. for commercial brands) from user-generated content (e.g. from reviews and comments; Pang and Lee, 2008). However, such technique is still underutilized in conservation science (Toivonen et al., 2019), especially in studies that aim to assess people's attitudes towards and opinions on species and their reactions to events related to their conservation (Drijfhout et al., 2016). Previous studies, which did not use natural language processing methods, have assessed how conservation issues are depicted in television and movies (Mitman, 1999), in news media (Jacobson et al., 2012; Muter et al.,

* Corresponding author at: Helsinki Lab of Interdisciplinary Conservation Science, Department of Geosciences and Geography, University of Helsinki, 00560, Helsinki, Finland.

*E-mail address:* christoph.fink@helsinki.fi (C. Fink).

https://doi.org/10.1016/j.biocon.2019.108289
Received 25 March 2019; Received in revised form 2 October 2019; Accepted 10 October 2019


Please cite this article as: Christoph Fink, Anna Hausmann and Enrico Di Minin, Biological Conservation, https://doi.org/10.1016/j.biocon.2019.108289

2013), in online search patterns (Nghiem et al., 2016), and social media (Büscher and Igoe, 2013; Hawkins and Silver, 2017) Previous studies have also investigated media responses to conservation events that are known to have caused large public responses, and the spatial and temporal characteristics of these responses (e.g. the killing of Cecil the lion, Macdonald et al., 2016; and the largest ivory destruction event to date, Braczkowski et al., 2018). To our knowledge, no previous study has attempted to automatically detect, identify and describe such events by investigating the reaction of the public and its change over time, using sentiment analysis (Drijfhout et al., 2016).

In this study, we investigated how sentiment analysis of social media and online news content can be used to monitor and study the reactions of the public to the conservation of iconic species. Our goal was to analyze spatio-temporal variation in volume and sentiment of text content pertaining to rhinoceros species on Twitter and in online news and assess which events triggered significant reactions, and were meaningful to the public. We focused on rhinoceros species because they are highly charismatic (Leader-Williams and Dublin, 2000), three (black rhinoceros *Diceros bicornis*, Javan rhinoceros *Rhinoceros sondaicus*, and Sumatran rhinoceros, *Dicerorhinus sumatrensis*) out of five species (including white rhinoceros *Ceratotherium simum* and Indian rhinoceros *Rhinoceros unicornis*) are critically endangered (IUCN, 2019), and all five species are listed in Appendix I of CITES (CITES, 2017) since they are highly threatened by illegal wildlife trade. Rhinoceros are in the focus of on-going conservation efforts (e.g. anti-poaching initiatives) and at the center of a public debate on policy-making (Di Minin et al., 2015a). In South Africa, the number of rhinos killed illegally for their horn has increased an alarming 10 000 % over less than a decade and controversial measures, such as legalizing the trade in horn, have been proposed to stop poaching (Di Minin et al., 2015a), sparking both positive and negative public reactions and extensive discussions on the media, which can be tracked using online data sources. Specific objectives were to (i) automatically classify sentiment of text content on Twitter and online news; (ii) assess spatio-temporal variations in volume and sentiment of posts; and (iii) identify which events triggered the biggest reactions.

## 2. Methods

### 2.0.1. Data collection

We selected two data sources representative of social media and online news. Twitter is a short-message platform, which has been in operation since 2006, and has around 67 million active users internationally (Statista, 2019). The service allows users to post 280 character long messages (140 before September 2017), and is one of the most prominent online outlets for political statements and debates, and opinion leading (Park, 2013). Twitter is often chosen as a primary source of information to study political opinion building on social media. Webhose is a service offering a *News Feed API* (application programming interface) providing "comprehensive […] coverage of news articles" (https://webhose.io/products/news-feeds/). We devised a data collection framework to continuously retrieve new posts pertaining to the keywords "rhinoceros" or "rhino" from the APIs of Twitter (basic search API) and Webhose, and perform sentiment analysis on all data (cf. Fig. A1 in Appendix). We chose to focus on the year 2018 for the present study as many events that might have triggered reactions by the public happened over this time period. The entire data set for 2018 contained 142 517 Twitter posts and 85 256 online news items. The average daily volume amounts to 390.5 ± 306.3 Twitter posts and 233.6 ± 135.7 online news items.

### 2.1. Sentiment analysis

The *sentiment* of a text means the overall attitude expressed in a text. Typically, sentiment is reported as the membership to one of the classes "positive", "neutral", or "negative", and is assessed on the literal meaning of a text. The sentence "Rhinoceros are amazing creatures" expresses a positive sentiment, "It's a shame what we do to these animals!" expresses a negative sentiment. Most recent models are trained on large datasets of texts that were categorized manually. They report a probability of membership to each of the classes for each text by assigning sentiment values to words and combining these values following complex grammatical, syntactical and contextual rules (see Hovy, 2015 for more details). Such models replicate the perception of the human operators who created the manual classification. Both models used in this study, *VADER* (Hutto and Gilbert, 2014) and *Webis* (Hagen et al., 2015), are openly accessible, pre-trained models for sentiment analysis.

We restricted sentiment identification to posts that we could identify to be in English language. We did this by (i) cleaning the text of all emojis, hashtags and user names, (ii) tokenizing (i.e. splitting into meaningful pieces, i.e. sentences and words) the text using the *spacy* Python module for natural language processing (Honnibal and Montani, 2017), (iii) using *FastText* (Joulin et al., 2016) to identify the language of the text, and (iv) extracting posts for which English language was predicted with an accuracy higher than 70%, a threshold chosen iteratively, and discarding the rest.

Since sentiment analysis models learn from manually classified data, it is important to ensure training data and analyzed data are similar in length, style and type of text. The different nature of the data sources required the use of different sentiment analysis algorithms for social media and online news data. The sentiment of online news text was assessed using *VADER* (Hutto and Gilbert, 2014), a leading general-purpose sentiment analysis tool. For Twitter data, characterized by short text lengths and extensive use of colloquial language, we used the highly specialized *Webis* sentiment evaluation tool (Hagen et al., 2015), which reached the highest classification accuracy for Twitter posts in an evaluation of "the state-of-the-art in Twitter sentiment analysis" (Zimbra et al., 2018). Both tools report the sentiment of a text in the classes *positive*, *negative*, or *neutral*.

The decision to use *VADER* for online news and *Webis* for Twitter posts was further confirmed when we carried out an evaluation of classification accuracy on a *gold standard* data set of 100 manually classified posts of each data source. For classification tasks, accuracy is commonly reported using precision, recall and f-score values (Chinchor, 1992), with the latter two being estimates of completeness and sensitivity, respectively. Across all classes (positive, negative, neutral), *Webis* sentiment classification for Twitter posts reached a precision of 0.809 (recall 0.826, f-score 0.814), and 0.517 (recall 0.306, f-score 0.288) for online news. *VADER*, in contrast, reached a precision of 0.806 (recall 0.879, f-score 0.838) for online news, and 0.368 (recall 0.843, f-score 0.654) for social media posts. For detailed per-class accuracy measures see Table 1.

### 2.2. Identifying main events in data

We calculated daily sums and mean sentiment, on a range of [-1; 1] between negative and positive, for social media posts and online news text separately. We then used an outlier detection technique to identify events that diverged from the overall pattern in both volume and sentiment. We used *Python 3.7.2* and *SciPy 1.2.1* to identify outliers, which were defined as greater than $Q3 + (1.5 \times IQR)$ or lower than $Q1 - (1.5 \times IQR)$, where Q1 and Q3 are the first and third quartile, respectively, and IQR is the interquartile range. We then identified the main topic for each outlier by (i) ranking social media posts by popularity (re-tweets, likes), (ii) manually identifying prevailing topics from news items' headlines, and (iii) carrying out a manual web search confined to the date of each outlier. Finally, we calculated pairwise temporal cross-correlations between all four time series using a custom *Python* implementation, equivalent to *R*'s `ccf` function (see Fig. A3 in Appendix for its source code).

**Table 1**
Sentiment classification accuracy measures.

| Data source | Sentiment Identification Algorithm | Class (sentiment) | Precision | Recall | F-score |
|---|---|---|---|---|---|
| Twitter | Webis | positive | 0.800 | 0.909 | 0.852 |
| | | neutral | 0.824 | 0.700 | 0.756 |
| | | negative | 0.805 | 0.868 | 0.836 |
| | | **avg/total** | **0.809** | **0.826** | **0.814** |
| | VADER | positive | 0.600 | 0.818 | 0.692 |
| | | neutral | 0.024 | N/A | N/A |
| | | negative | 0.478 | 0.868 | 0.616 |
| | | **avg/total** | **0.368** | **0.843** | **0.654** |
| Online news | Webis | positive | 0.800 | 0.105 | 0.186 |
| | | neutral | 0.043 | 0.286 | 0.074 |
| | | negative | 0.707 | 0.527 | 0.604 |
| | | **avg/total** | **0.517** | **0.306** | **0.288** |
| | VADER | positive | 0.745 | 0.921 | 0.824 |
| | | neutral | N/A | N/A | N/A |
| | | negative | 0.868 | 0.836 | 0.852 |
| | | **avg/total** | **0.806** | **0.879** | **0.838** |

### *2.3. Geographical distribution and daily variation*

To give an overview of the global geographical distribution of social media posts and of daily temporal variation, at local time, we mapped this data by time zones, resulting in a combined map and chart. As the Twitter API does not provide the local time of posts, we inferred this information by using a post's georeference or, if not available, the location specified in the user's profile information. This is the most precise time zone information available across all posts. Using time zones as a reference unit allowed us to avoid some of the common pitfalls concerning accuracy, precision, and completeness of georeference data attached to social media posts (see Graham et al., 2014). We calculated sums per time zone and local hour of the day and plotted this data using *matplotlib 3.0.3* on *Python 3.7.2.* We then used *QGIS 3.4.4* to visualize the reported locations of georeferenced posts. Time zones were rounded to full hours to make the figure more accessible.

## 3. Results

The global distribution of social media posts pertaining to rhinoceros species, and its diurnal variation per each time zone, is illustrated in Fig. 1. The map (Fig. 1a) shows that *rhinoceros* and *rhino* seem to be topics especially prevalent in (i) Western Europe – in particular the United Kingdom –, the United States, and Australia, and (ii) in some rhinoceros range countries in Africa (South Africa, Kenya) and Asia (Indonesia, Malaysia). This corresponds to the absolute counts of posts per time zone (Fig. 1b) which show a majority of posts originating from the UTC (United Kingdom), -8 to -4 (North America), +8 (Indonesia) and +1 (Western Europe) time zones. There is local variation in the daily temporal patterns (Fig. 1c): post counts were higher during daytime hours almost universally across all time zones. The volumes in Asian, African and European time zones peak in the afternoon, while the American time zones see a maximum late in the morning. Globally (Fig. 1d), most social media content is posted in the afternoon, while the minimum value is reached during night time. Online news data exhibit a similar pattern, see Fig. A2 in Appendix for a map of the global distribution of online news items pertaining to *rhinoceros* and *rhino*.

Specific events appear to have triggered increases in both volume and mean sentiment of social media and online news (Fig. 2, full list of identified events in Table 2). The mean sentiment over the entire time series was slightly positive (0.041 ± 0.237 on a scale [-1; 1]) for Twitter, and pronouncedly positive (0.305 ± 0.224) for online news data. On 20 March 2018, following the passing of *Sudan*, the last male northern white rhinoceros (*Ceratotherium simum cottoni*), the previous day, the volume of tweets exceeded the average by more than five

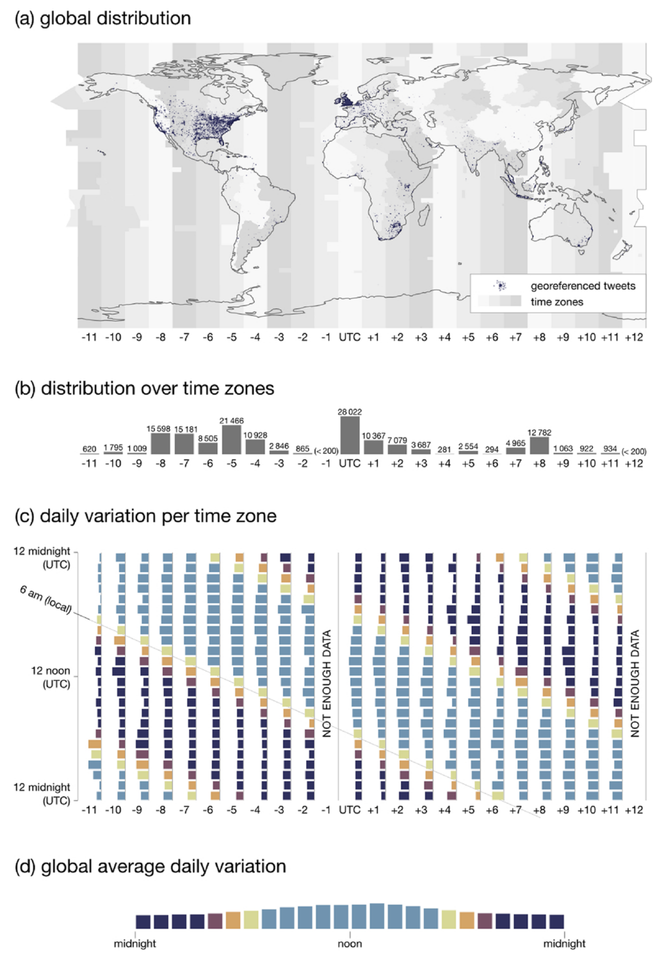


**Fig. 1.** Social media posts pertaining to *rhinoceros* species: (a) global distribution, (b) distribution over time zones, (c) daily variation per time zone, at local time, and (d) global average daily variation. The colors of the bars in (c) and (d) represent the time of the day (use (d) as a legend), the size of the bars show the count of posts in a particular hour of the day and are scaled relatively to the maximum value of a series. Data sources: Twitter API, Natural Earth Data.

times; the count of news items published was the highest of any day in the entire research period. For this event, mean Twitter sentiment was highly negative. On 30 April 2018, the volume of online news increased strongly, together with its mean sentiment deflecting considerably towards positive, related to press reports on UK royals Prince Harry and his then fiancée Meghan Markle's visit to Botswana. The event did not affect Twitter posting. On 13 July 2018, media reports of the death of critically endangered eastern black rhinoceros (*Diceros bicornis michaeli*) translocated to Tsavo National Park, Kenya, caused the values of both sentiment and volume of online news to increase significantly. On 15 July 2018, Twitter sentiment was exceedingly negative, all other characteristics remaining within average values, in relation to a post that was retweeted 400 times and referred to the extinction of the western black rhinoceros (*Diceros bicornis longipes*). Mean sentiment is also high for a prolonged period of time in the second half of June (Fig. 2), due to a social media campaign by the Indian Ministry of Tourism that partly focused on Indian rhinoceros (*Rhinoceros unicornis)*.

We also carried out temporal cross-correlations of the four time series (Fig. 3). We found a strong cross-correlation between Twitter volume and online news volume (Fig. 3a), at lags 0, -1, -2 (i.e. news items posted at the same or the two previous days as a tweet). The mean sentiment of the two data sources correlates above 0.95 confidence interval (Fig. 3e). Twitter sentiment correlates at a highly significant level (0.99) with Twitter volume (Fig. 3f). The sentiment of online news


**Fig. 2.** The daily counts and mean sentiment of Twitter posts and online news items pertaining to *rhinoceros* species from March to July 2018. Data was obtained from the Twitter and webhose.io *application programming interfaces* (API). Outliers were calculated by categorizing values $> \mathtt{Q3} + 1.5\ \mathtt{IQR}$ and $< \mathtt{Q1} - 1.5\ \mathtt{IQR}$ as outliers, where $\mathtt{Q1}$ and $\mathtt{Q3}$ are the first and third quartile and IQR is the interquartile range.

**Table 2**
Events identified from social media and online news data in Fig. 1.

| Month | Day(s) | Outliers in | | | | Event |
|---|---|---|---|---|---|---|
| | | Twitter volume | Twitter sentiment | Online news volume | Online news sentiment | |
| March | 2-5 | | ↑ | | | New-born white rhinoceros in zoo in the Netherlands |
| | 16 | | | ↑ | | Trump wildlife protection board defends trophy hunting |
| | 20 | ↑ | ↓ | ↑ | | Reactions to the death of Sudan, the last male northern white rhinoceros |
| | 21-23 | ↑ | | | | 〃 |
| April | 4 | | | | ↑ | Baby rhinoceros defends mother from vet |
| | 30 | | | ↑ | ↑ | Prince Harry and Meghan Clark visit Botswana |
| May | 7-9 | | ↑ | | | Woolly rhinoceros found in Siberia |
| | 17 | | | ↑ | | White rhinoceros pregnant through artificial impregnation (San Diego Zoo) |
| June | 2 | | ↑ | | | Tweet addressing the Prime Minister of India, expressing pride in the survival of the one-horned rhinoceros in Assam |
| | 10, 13-16, 23-26,29, 30 | | ↑ | | | @IncredibleIndia tourism campaign video mentioning one-horned rhino |
| | 12 | ↑ | | | | 〃 |
| | 23 | | | | ↑ | (no distinct event identifiable) |
| July | 5 | ↑ | | | | CNN: in-vitro fertilization for “hybrid rhino” |
| | 6 | | | ↑ | | Poachers mauled to death by lions in Sibuya game reserve, South Africa |
| | 13 | | | ↑ | | Eight out of eleven recently translocated rhinos reported dead in Tsavo National Park, Kenya |
| | 15 | | ↓ | | | Bill Nye: “I aint been the same since west african black rhino went extinct” |
| | 27 | | ↓ | | | Negative remark about insects “except rhinoceros beetles” |
| | 30 | ↑ | ↓ | ↑ | ↓ | Negative remark about insects “except rhinoceros beetles” (Twitter), first post-Mugabe elections in Zimbabwe (online news) |

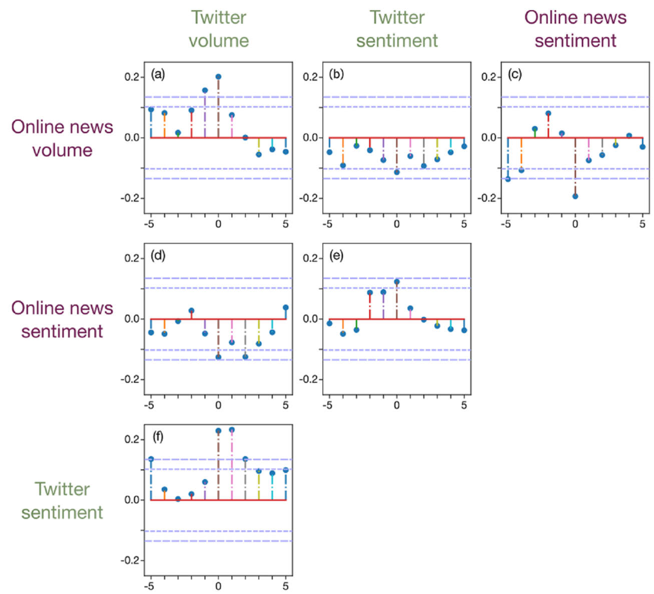


**Fig. 3.** Temporal cross-correlation of social media and online news content pertaining to rhinoceros species. Data obtained from Twitter and webhose.io *application programming interfaces* (API). The x-axes represent a lag in days (0 = same day), y-axes the cross-covariance between the respective column and row. The blue dashed lines show confidence intervals of 0.95 and 0.99, respectively. Explanation on how volume and sentiment were assessed is available in the *Methods*. Note that a high temporal correlation between volume and sentiment can be interpreted as “the more posts, the less neutral the sentiment”.

shows a significant negative correlation with its volume (Fig. 3c). Twitter sentiment and online news sentiment both show a significant negative correlation with the volume of the respective other data source (Fig. 3b, d). The sentiment of the two data sources shows a significant positive correlation (Fig. 3e). High temporal correlation between the post volume and the mean sentiment means “the more posts, the less neutral the sentiment expressed”, potentially confirming that increases in posting volume are triggered by major events rather than by many minor events together.

## 4. Discussion

In this study, we examined reactions towards events related to rhinoceros conservation on Twitter and online news. In comparison to previous similar studies looking at the online discourse around the conservation of a threatened species (see e.g. Harrington et al., 2018), our approach allowed us to identify the sentiment attached to public reaction, and proved to be more reliable in identifying conservation-related events. We found that it is especially negative events, such as the local extinctions of two sub-species of rhinoceros in Africa, which caused substantial public reaction, both in terms of total number of posts and articles, and sentiment expressed therein. In contrast, positive events seem to be underrepresented. For instance, the initially positive media coverage of the translocation of rhinoceros to Tsavo National Park in Kenya did not register as an outlier in our data, and was drastically overshadowed by the reactions to the later failure of the operation. Certain events, on the other hand, appear to be platform-specific and are, for instance, shared on social media or online news only. In line with Braczkowski et al. (2018), we found that the strongest reactions on Twitter originate in Western countries and not from within rhinoceros range countries. This might be partly due to the presence of prominent conservation non-governmental organizations (NGOs) in these countries (but this requires more research in the future, for instance by looking separately at the temporal patterns of the social media accounts of the most important NGOs). The largest part of Twitter status messages referring to *rhinoceros* and *rhino* was posted during working hours, which might indicate a strong interest in the species and their conservation (warranting a break from work to post), or a sizable share of corporate actors involved in the discourse, such as active marketing campaigns by NGOs. While social media data and online news come with a certain degree of uncertainty (e.g. data sparseness and representativeness; Toivonen et al., 2019) we argue that the methods presented here can be used to follow conservation related events on all digital data sources that make data openly available.

Different types of events triggered different reactions. The differences can be found not only between “traditional” online news and social media, but also between a data source’s volume and its mean sentiment. The volume – a simple count per unit of time – represents a quantitative measure of the attention an event receives; the sentiment – a complex estimation of feelings and opinions expressed in a (written) text –, in turn, measures the quality, or intensity, of this attention. It is also the correlation between post volume and mean sentiment (i.e. the more posts the less neutral the sentiment) that allowed us to identify influential events. Mean sentiment, in fact, would deflect towards neutral if the increase in post volume were to derive from multiple topics.

Depending, among other things, on its perceived severity and urgency, its general scope, and the “emotional value” attached to it, a given conservation event might be identifiable from one of sentiment or volume only. We argue further that the magnitude of a conservation-related event and societal importance can be estimated from the combined reading of both measurements. For instance, the reactions to *Sudan’s* (the last male northern white rhinoceros) death, arguably the most significant widely publicized events related to rhinoceros conservation in 2018, triggered reactions both in terms of volume and sentiment, both on social media and in online news. In contrast, Prince Harry’s visit to Botswana was only loosely connected to rhinoceros conservation and was not picked up by social media at all. These results reinforce the importance of using multiple data sources in digital conservation (see e.g. Cooper et al., 2019).

While the research design aimed to measure public interest in and engagement with a broader area of biodiversity conservation, the main event found in the data of this study is the biological extinction of a subspecies and reactions to it. Our results appear to confirm that societal groups of a European descent might be feeling most affected or guilty about extinctions (Ladle and Jepson, 2008). Cultural-geographical differences might also explain the low number of tweets and news items from African and Asian rhinoceros range countries. Still, other factors, such as different internet or media usage patterns (use of other social media platforms or lower representation in our dataset of other online media outlets) might be drivers of these geographical differences. In general, social media data – and to a certain extent online news data – are subject to issues of representativeness, data collection biases and “echo chambers” (groups of users with similar world views reinforcing and reproducing common narratives) that amplify certain discussions and elevate them over others (Driscoll and Walker, 2014; Tufekci, 2014). Attention has to be paid to the georeference of digital data, which can lack in accuracy, precision and completeness (Graham et al., 2014). We aggregated data to time zones and countries to avoid these pitfalls. Future research should also consider the effects of such biases on assessing the public reaction to conservation topics.

We found significant correlations between time series of daily counts and daily mean sentiment. Daily Twitter volume seems to follow daily online news volume. This might well be explained by the common practice of news articles being promoted, shared and distributed on social media, which also explains the significant correlation between tweet volume and the respective previous day’s online news volume. The fact that online news sentiment is showing a similar correlation to Twitter volume as to online news volume suggests that online news content is largely covered by Twitter content. Twitter sentiment, on the contrary, shows an inverse correlation for the two data sources’ volumes, suggesting that Twitter might provide content that online news do not provide. The strong negative correlation between online news' volume and sentiment, in turn, lead us to speculate whether news outlets are more readily picking up negative news items than positive ones, or that 2018′s predominant rhinoceros-related news items might have been of a negative nature. Indeed, the most reported events were the biological extinction of a sub-species with the death of the last male northern white rhinoceros, and the failed translocation of the critically endangered black rhinoceros to Tsavo National Park, Kenya.

## 5. Conclusion

We demonstrated that natural language processing techniques, established in other fields, can be successfully used in conservation science. The temporal variation of public sentiment and of the volume of content pertaining to a topic can be used to identify events, which trigger public reaction, and assess the polarity of such reaction. The two data sources used in this study, social media and online news, complement each other, and should be used jointly when possible. Overall, our results can be used to help develop enhanced strategies for the conservation of rhinoceros species that consider reactions of the general public, for instance in support of fundraising activities to prevent species' extinctions (certain causes might seem more important to the public than others). Identifying such reactions could also be used to increase pressure on decision makers to develop adequate conservation strategies and to allocate adequate resources for conservation, by demonstrating how broad and assertive public support for a cause is. The magnitude of the public outcry after Sudan's death is a clear example. Similar strategies have been observed to be successful, for instance, in persuading politicians to pledge for climate change engagement (Anderson, 2017).

The results also highlight that public reactions are currently missing from people in rhinoceros range countries, who bear the highest costs of rhinoceros conservation. While this result is not surprising, it is highly relevant, and its effects might be attributed to a digital divide and to different online platforms being used in different parts of the world, highlighting that future studies should focus on better assessing reactions from rhinoceros range countries.

While the methods were applied here to assess public sentiment for iconic species, they can be used for any other biodiversity-related content, although more research is needed in respect to topics exhibiting a lower base-line of public interest, and in respect to topics covering broader taxonomic groups. To our knowledge we were able to identify all major events related to rhinoceros conservation over the study period. However, this might prove more challenging for less prominent topics or for less charismatic species. The same methods can be used to measure the effects of outreach campaigns and education programs, to gather feedback on conservation tourism (e.g. reactions to changes in regulations or infrastructure), or to measure reactions to policy changes. Conservation managers and authorities could also more easily react to online "conservation violence", such as the outright open calls for militarized violence against poachers and the demands to deny poachers Human Rights as described by Lunstrum (2017), if they were made aware of such posts in a timely manner. Our study shows that we have the capacity to do real-time monitoring of sentiment for species or places of conservation importance, e.g. protected areas. Combined with existing conservation culturomics methods, such as for assessing digital salience (e.g. web page counts, Correia et al., 2017) and measuring public interest (e.g. Wikipedia page views, Mittermeier et al., 2019), this approach can provide a deeper understanding of the impact of conservation campaigns (for fundraising or policy-making), and of societal support for conservation actions. Our automated system can be used to collect and analyze data continuously and to detect changes in public opinion in near real-time, providing continuous guidance to conservation managers and policy makers, who can react quicker and more pro-actively, targeting social media campaigns and press releases to address the prevailing concerns of the public.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Acknowledgements

The authors thank Laura Centore for early work and discussions on a related topic. The authors thank three anonymous reviewers for valuable comments that helped improve the manuscript. CF thanks the University of Helsinki for an early career grant to EDM. EDM thanks the Academy of Finland, grant#295624, for support. AH thanks the Helsinki Institute of Sustainability Science (HELSUS) for funding to EDM. EDM and AH thank the European Research Council (ERC) for funding under the European Union's Horizon 2020 research and innovation program (grant agreement#802933).

## Appendix A

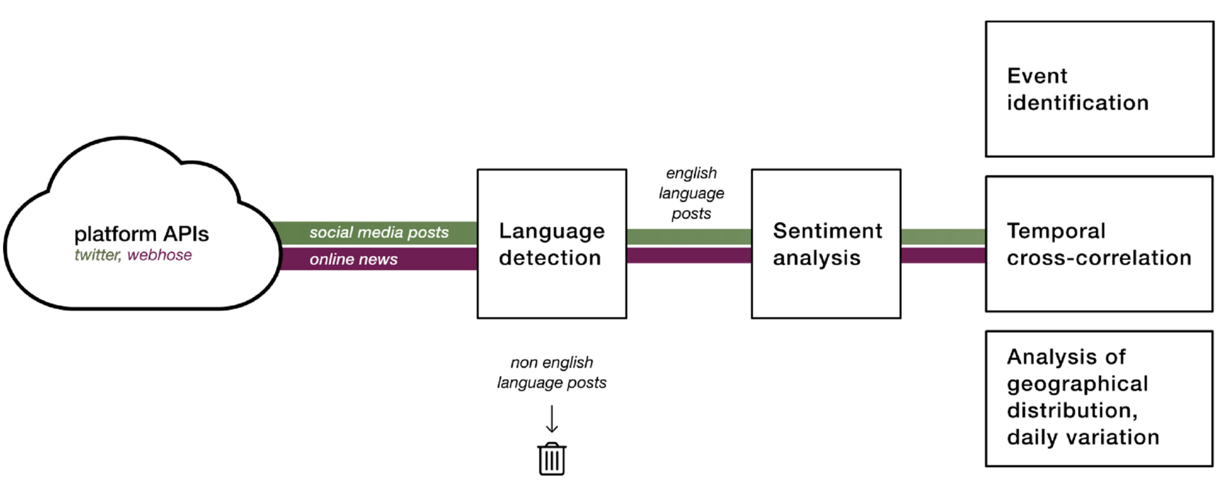


**Fig. A1.** The workflow of the data collection and processing framework.

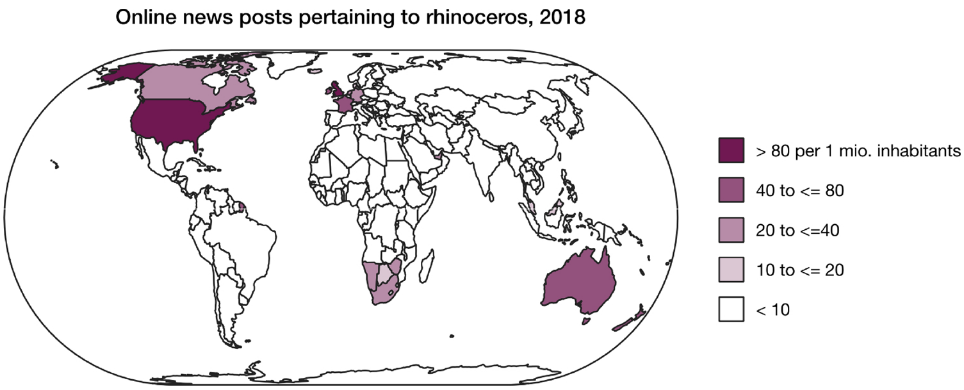


**Fig. A2.** Posts on online news pertaining to rhinoceros species. Online news data was obtained from the Webhose application programming interface using a custom *Python 3.7.2* implementation (see *Methods*); these data contain information on the country the news outlet publishing a news item is based in; sums per country were calculated using *PostgreSQL 11.2/PostGIS 2.5* and visualized using *QGIS 3.4.4*. Data sources: Webhose, Natural Earth Data.

```
import numpy
import scipy.signal
import scipy.stats

def ccf(x, y):
    ccf = scipy.signal.correlate(
        x - numpy.mean(x),
        y - numpy.mean(y),
        method="direct"
    ) / (numpy.std(x) * numpy.std(y) * len(x))

    ci95 = scipy.stats.norm.ppf((1 + 0.95) / 2) /
math.sqrt(len(x))
    ci99 = scipy.stats.norm.ppf((1 + 0.99) / 2) /
math.sqrt(len(x))
```

**Fig. A3.** Custom *Python 3.7.2* (*SciPy 1.2.1*, *NumPy 1.16.2*) `ccf` function used for calculating temporal cross-correlation between volume and sentiment of social media and online news content. Adapted from https://stackoverflow.com/questions/53959879/how-do-i-get-rs-ccf-in-python.

## References


Anderson, A.A., 2017. Effects of social media use on climate change opinion, knowledge, and behavior. Oxford Research Encyclopedia of Climate Science. https://doi.org/10.1093/acrefore/9780190228620.013.369.

Arts, K., van der Wal, R., Adams, W.M., 2015. Digital technology and the conservation of nature. Ambio 44, 661–673. https://doi.org/10.1007/s13280-015-0705-1.

Braczkowski, A., Holden, M.H., O'Bryan, C., Choi, C.-Y., Gan, X., Beesley, N., Gao, Y., Allan, J., Tyrrell, P., Stiles, D., Brehony, P., Meney, R., Brink, H., Takashina, N., Lin, M.-C., Lin, H.-Y., Rust, N., Salmo, S.G., Watson, J.E.M., Kahumbu, P., Maron, M., Possingham, H.P., Biggs, D., 2018. Reach and messages of the world's largest ivory burn. Conserv. Biol. 32, 765–773. https://doi.org/10.1111/cobi.13097.

Büscher, B., Igoe, J., 2013. Prosuming' conservation? Web 2.0, nature and the intensification of value-producing labour in late capitalism. J. Consum. Cult. 13, 283–305. https://doi.org/10.1177/1469540513482691.

Chinchor, N., 1992. MUC-4 Evaluation Metrics. Proceedings of the 4th Conference on Message Understanding, MUC4 '92. Association for Computational Linguistics, Stroudsburg, PA, USA, pp. 22–29.

Chowdhury, G.G., 2005. Natural language processing. Ann. Rev. Info. Sci. Tech. 37, 51–89. https://doi.org/10.1002/aris.1440370103.

CITES, 2017. CITES Appendix I, Version From April 2017.

Cooper, M.W., Di Minin, E., Hausmann, A., Qin, S., Schwartz, A.J., Correia, R.A., 2019. Developing a global indicator for Aichi Target 1 by merging online data sources to measure biodiversity awareness and engagement. Biol. Conserv. 230, 29–36. https://doi.org/10.1016/j.biocon.2018.12.004.

Correia, R.A., Jepson, P., Malhado, A.C.M., Ladle, R.J., 2017. Internet scientific name frequency as an indicator of cultural salience of biodiversity. Ecol. Indic. 78, 549–555. https://doi.org/10.1016/j.ecolind.2017.03.052.

Di Minin, E., Fink, C., Hiippala, T., Tenkanen, H., 2019. A framework for investigating illegal wildlife trade on social media with machine learning. Conserv. Biol. 33, 210–213. https://doi.org/10.1111/cobi.13104.

Di Minin, E., Fink, C., Tenkanen, H., Hiippala, T., 2018. Machine learning for tracking illegal wildlife trade on social media. Nat. Ecol. Evol. 2, 406–407. https://doi.org/10.1038/s41559-018-0466-x.

Di Minin, E., Laitila, J., Montesino-Pouzols, F., Leader-Williams, N., Slotow, R., Goodman, P.S., Conway, A.J., Moilanen, A., 2015a. Identification of policies for a sustainable legal trade in rhinoceros horn based on population projection and socioeconomic models. Conserv. Biol. 29, 545–555. https://doi.org/10.1111/cobi.12412.

Di Minin, E., Tenkanen, H., Toivonen, T., 2015b. Prospects and challenges for social media data in conservation science. Front. Environ. Sci. 3. https://doi.org/10.3389/fenvs.2015.00063.

Drijfhout, M., Kendal, D., Vohl, D., Green, P.T., 2016. Sentiment Analysis: ready for conservation. Front. Ecol. Environ. 14, 525–526. https://doi.org/10.1002/fee.1435.

Driscoll, K., Walker, S., 2014. Working within a black box: transparency in the collection and production of big Twitter data. International Journal of Communication 8, 20.

Graham, M., Hale, S.A., Gaffney, D., 2014. Where in the world are you? Geolocation and language identification in Twitter. Prof. Geogr. 66, 568–578. https://doi.org/10.1080/00330124.2014.907699.

Hagen, M., Potthast, M., Büchner, M., Stein, B., 2015. Webis: an ensemble for twitter sentiment detection. Proceedings of SemEval.

Harrington, L.A., D'Cruze, N., Macdonald, D., 2018. Rise to fame: events, media activity and public interest in pangolins and pangolin trade, 2005–2016. NC 30, 107–133. https://doi.org/10.3897/natureconservation.30.28651.

Hawkins, R., Silver, J.J., 2017. From selfie to #sealfie: nature 2.0 and the digital cultural politics of an internationally contested resource. Geoforum 79, 114–123. https://doi.org/10.1016/j.geoforum.2016.06.019.

Honnibal, M., Montani, I., 2017. spaCy 2: natural language understanding with bloom embeddings, convolutional neural networks and incremental parsing to Appear.

Hovy, E.H., 2015. What are sentiment, affect, and emotion? Applying the methodology of Michael Zock to sentiment analysis. In: Gala, N., Rapp, R., Bel-Enguix, G. (Eds.), Language Production, Cognition, and the Lexicon. Springer International Publishing, Cham, pp. 13–24.

Hutto, C.J., Gilbert, E., 2014. VADER: a parsimonious rule-based model for sentiment analysis of social media text. 8th International Conference on Weblogs and Social Media 10.

IUCN, 2019. The IUCN Red List of Threatened Species. Version 2019-1.

Jacobson, S.K., Langin, C., Carlton, J.S., Kaid, L.L., 2012. Content analysis of newspaper coverage of the Florida panther. Conserv. Biol. 26, 171–179. https://doi.org/10.1111/j.1523-1739.2011.01750.x.

Joulin, A., Grave, E., Bojanowski, P., Mikolov, T., 2016. Bag of Tricks for Efficient Text Classification. arXiv:1607.01759 [cs].

Ladle, R.J., Correia, R.A., Do, Y., Joo, G.-J., Malhado, A.C., Proulx, R., Roberge, J.-M., Jepson, P., 2016. Conservation culturomics. Front. Ecol. Environ. 14, 269–275.

https://doi.org/10.1002/fee.1260.
Ladle, R.J., Jepson, P., 2008. Toward a biocultural theory of avoided extinction. Conserv. Lett. 1, 111–118. https://doi.org/10.1111/j.1755-263X.2008.00016.x.
Leader-Williams, N., Dublin, H.T., 2000. Charismatic megafauna as "flagship species. In: Entwistle, A., Dunstone, N. (Eds.), Priorities for the Conservation of Mammalian Diversity: Has the Panda Had Its Day? Cambridge University Press, pp. 53–84.
Li, H., 2018. Deep learning for natural language processing: advantages and challenges. Sci. Rev. 5, 24–26. https://doi.org/10.1093/nsr/nwx110.
Liu, B., 2012. Sentiment analysis and opinion mining. Synth. Lect. Hum. Lang. Technol. 5, 1–167. https://doi.org/10.2200/S00416ED1V01Y201204HLT016.
Lunstrum, E., 2017. Feed them to the lions: conservation violence goes online. Geoforum 79, 134–143. https://doi.org/10.1016/j.geoforum.2016.04.009.
Macdonald, D., Jacobsen, K., Burnham, D., Johnson, P., Loveridge, A., 2016. Cecil: a moment or a movement? Analysis of media coverage of the death of a lion, Panthera leo. Animals 6, 26. https://doi.org/10.3390/ani6050026.
Mitman, G., 1999. Reel nature: America's romance with wildlife on film. Harvard University Press, Cambridge, MA.
Mittermeier, J.C., Roll, U., Matthews, T.J., Grenyer, R., 2019. A season for all things: phenological imprints in Wikipedia usage and their relevance to conservation. PLoS Biol. 17, e3000146. https://doi.org/10.1371/journal.pbio.3000146.
Muter, B.A., Gore, M.L., Gledhill, K.S., Lamont, C., Huveneers, C., 2013. Australian and U.S. news media portrayal of sharks and their conservation. Conserv. Biol. 27, 187–196. https://doi.org/10.1111/j.1523-1739.2012.01952.x.
Nghiem, L.T.P., Papworth, S.K., Lim, F.K.S., Carrasco, L.R., 2016. Analysis of the capacity of Google Trends to measure interest in conservation topics and the role of online news. PLoS One 11, e0152802. https://doi.org/10.1371/journal.pone.0152802.
Pang, B., Lee, L., 2008. Opinion mining and sentiment analysis. Foundations and Trends in Information Retrieval Vol. 2. pp. 1–135.
Park, C.S., 2013. Does Twitter motivate involvement in politics? Tweeting, opinion leadership, and political engagement. Comput. Human Behav. 29, 1641–1648. https://doi.org/10.1016/j.chb.2013.01.044.
Statista, 2019. Number of Monthly Active Twitter Users in the United States From 1st Quarter 2010 to 4th Quarter 2018 (in Millions) [WWW Document]. URL https://www.statista.com/statistics/274564/monthly-active-twitter-users-in-the-united-states/ (accessed 2.27.19). .
Toivonen, T., Heikinheimo, V., Fink, C., Hausmann, A., Hiippala, T., Järv, O., Tenkanen, H., Di Minin, E., 2019. Social media data for conservation science: a methodological overview. Biol. Conserv. 233, 298–315. https://doi.org/10.1016/j.biocon.2019.01.023.
Tufekci, Z., 2014. Big questions for social media big data: representativeness, validity and other methodological pitfalls. ICWSM 14, 505–514.
Zimbra, D., Abbasi, A., Zeng, D., Chen, H., 2018. The state-of-the-art in Twitter sentiment analysis: a review and benchmark evaluation. ACM Trans. Manag. Inf. Syst. 9, 1–29. https://doi.org/10.1145/3185045.